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Predicting Non-Newtonian Fluid Electric Submersible Pump failure using Deep Learning and Artificial Neural Network

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Abstract. The monitoring of electric submersible pumps (ESPs) is essential for optimal petroleum artificial lifting operations. Most ESP research are aimed at operation improvement and optimization of the centrifuge multi-stage pump motor and the load that the pump has to discharge which is a function of the pumps mechanical properties and characteristics, liquid compositions, pressure and temperature. ESPs failure often lead to oil production losses or “oil deferment” which affects revenue for all the parties involved. Also, pulling the ESP out of the wellbore of interest, requires mobilization of a rig because it is installed several hundred meters down the wellbore. To prevent these loses, a predictive approach is needed to avert these scenarios. In the current decade, machine learning algorithms studies have spurred real- time technologies research interest due to their abilities to predict future outcomes using already existing data sets. This study presents a predictive approach for Electric Submersible Pump failure during artificial lift operations. The study creates an “algorithm” that helps to predict via Machine learning, the failure of an ESP with the assumption that failure is usually caused by pressure build-ups. A deep learning model for predicting ESP failure was proposed and artificial neural network was used in developing the suggested model. Based on the outcomes of this study, it can be concluded that the selected AI algorithm and its characteristics, are suitable for applications in detecting ESP failure before it happens using upstream-data.

Keywords: Electric submersible pump; Deep learning; Artificial neural network; Pump discharge pressure; Non-Newtonian fluid

1. Introduction

Historically, submersible electric pumps (ESPs) have been used to remove liquids from mining sites. It then found application in hydrocarbon wells that produce large water with a little gas-oil ratio (GLR). To date, the application of ESPs in wells that has little water influx has been extended to most mature hydrocarbon fields were the natural reservoir energy cannot long provide the necessary drive for the hydrocarbon production. There are many examples in the literature where ESP is used in wells that produce very little water and a lot of gas [1]. ESPs are generally reserved for applications in which the generated or natural stream is mostly fluid. A huge volume of gas in the ESP can result in gas interference or serious damage if the ESP is not installed properly. Free gas can meaningfully cause a reduction in the load generated by the ESP and thwart the propelled fluid from getting to the surface. ESP design can be effective for gas reservoirs that also have substantial amount of fluids, because the liquids from the wellbore can be removed effectively to allow ease of gas flow to surface using the flow channels [3]. ESP applications have been also proven to be effective means of dewatering crude oil wells. The design and size of the impeller, the speed of rotation, capacity of the electric motor, pump capacity and characteristics and fluid thermodynamic properties have been identified as the source of ensuring effective performance and output capacity for ESPs [4, 5]. Thus, the performance efficiency of ESPs depends solely on the mechanical and fluid properties under consideration.

After the correct design of the submersible electric pump (ESP), operators often attempt to achieve the maximum possible service life. To achieve this, the equipment must be properly installed, and the operation of the device must be regularly maintained and monitored. Mature fields, tight and unconventional reservoirs experience significant and rapid flow drop with phase fraction changes [6]. Figure 1 shows the life run analysis of twenty-five (25) ESP used in "Field X" for production of hydrocarbon. The analysis showed that with proper installation, maintenance, and surveillance, about 60% of the ESP did not exceed three (3) years run life. Therefore, the routine monitoring of ESP operation parameters is considered a standard operation method not a guarantee for prolong run life [7].

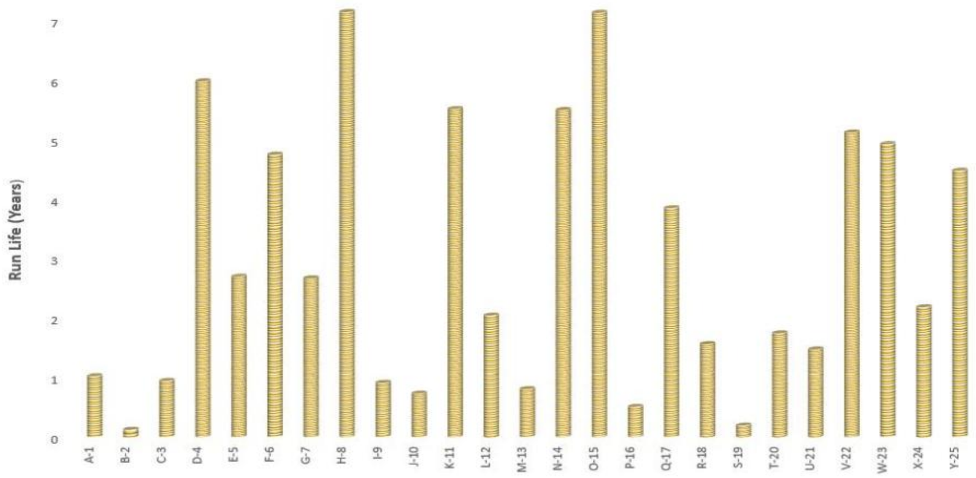

Figure 1. "Field X" ESP performance run life analysis for Hydrocarbon Wells

It is assumed that operating conditions are constant throughout the life of the well. However, performance changes over time and tends to decrease as the production life of the well increases [8]. Oil, gas and water ratio also change over time. EPSs are used in hydrocarbon exploration and production business to produce an unlimited volume of liquids from the hydrocarbon wellbores. According to Minette et al. [1], ESPs have been used to produce approximately 10% of the world's crude oil. ESP failures account for thousands of barrels of deferred production. For example, assuming deferring production from a well(s) producing 1,000 Boe for one (1) month with an oil price of $50. Complete failures often leads to a complete loss of the ESP functions, while partial failures leads to reduction in the ESP capacity. ESPs failures often lead to oil production losses or "oil deferment" which affects revenue for all the parties involved [9, 10]. Also, pulling the ESP out of wellbore requires mobilization of a rig because it is installed several hundred meters down the wellbore.

Most ESP research are aimed at operation improvement and optimization of the centrifuge multi-stage pump motor and the load that the pump has to discharge which is a function of the pumps mechanical properties and characteristics, liquid compositions, pressure and temperature [11, 12]. Although, Castellanos et al. [7] in their study applied classification and regression tree in the recognition and organization of pumping system incipient faults. This study creates an Algorithm that learns to predict when the ESP would fail with Machine learning, with the assumption that failure is usually caused by previous readings build-ups. A deep learning model for ESP failure prediction was proposed and neural network was utilized for constructing the suggested model. The development of modern oil and gas industry has caused highly increased complexity in both industrial equipment and production systems, which makes it challenging to identify and evaluate failure conditions in a timely manner with conventional methods. The development of an appropriate forecasting and inspection method to assess ESP mechanical damage and failure with a long warning period/ window is of paramount importance in the oil and gas industry. The ability and complexity of the deep learning algorithm is greatly enhanced due to the internal hierarchical structure; hence, its adoption in this study.

2. Methodology

The frequency of failure for electric submersible pumps in most mature oil field wells are a concern as shown in Figure 1. Hence, it is of utmost importance to develop techniques or tools that can effectively predict the ESPs lifetime. Most hydrocarbon wells are produced with an electric submersible pump (ESP) as an artificial lift method. These downhole ESPs are powered with on-site diesel generators or from the mains. The variable speed drive unit for the ESP is specific for the hydrocarbon wells, which can change the current rate and transform the pump speed to control the outcomes from the ESP. The frequency of ESP is often increased to make-up for the decreased oil production rate due to increased wellbore water influx. A distinctive allowable operating frequency range is from 30 to 70 Hz.

ESPs operational performance sequence is summarized below:

1. The pump head ΔH supplied by the ESP pump decreases with an increase in flow rate.
2. An increase in the impeller rotation rate produces a relative increment in the pump performance in accordance with the affinity rules (Equations (1 and 2), scaling with pump frequency).

The ESP efficiency usually decreases when working with fluids that are more viscous than water [13].

$$\frac{\Delta H_1}{\Delta H_{ref}} = \left(\frac{f_1}{f_{ref}}\right)^2 \tag{1}$$

$$\frac{q_1}{q_{ref}} = \frac{f_1}{f_{ref}} \tag{2}$$

Where, f_{ref} is the frequency of reference, usually 60 Hz and q_{ref} is the corresponding flow rate.

According to Hoffman and Stanko [13], “in order to avoid gas absorption in the ESP and cavitation, the suction pressure of the pump is often maintained above the minimum value, which depends on the pump’s work flow.” The methodology is based on an objective phenomenon: this phenomenon shows that when devices fail, they show various types of characters, and these fluctuations are recorded and captured in the data collected during this period, and this data can be used to record the precursors of the malfunction. Therefore, deep learning approach was applied to determine the maximum selective information concealed behand the acquired for diverse failure cases.

2.1 Proposed Production Optimization Method

There are numeric and model-based optimization schemes in literature that serves as advisory scheme to the operators. These advisory scheme often performs mathematical optimization on the network model to determine the optimum production frequency. These models consider a set of conservation equations for steady state that must be answered in an iterative approach to calculate the optimum conditions for production while neglecting all time dependent fluctuations.

But, this study proposed an electric submersible pump failure prediction model, that utilizes deep learning and artificial neural network with the assumption that failure is usually caused by previous readings build-ups. Python programming language, Keras - which is a library for deep learning and artificial neural network (long short term memory, LSTM) were applied in developing this model. LSTM networks belong to the class of recurrent neural networks (RNNs). In other words, a neural network in which the underlying topology of connections between neurons contains at least one cycle [14, 15]. LSTM network in its nature studies long-term colonies from data trends and can overcome the intrinsic problems of RNNs. An LSTM network consists of an input section, one or more storage locations, and an output section. The number of neurons in the input section corresponds to the number of explanatory variables. The main feature of LSTM networks is a hidden layer consisting of so-called memory cells. In this study, the preparation and transfer of data is completely done in Python using the Numpy and Pandas packages. The LSTM and ANN networks are established using Keras. LSTM is capable of modelling sequences of a model, in this study, time-sequences because the data set contained values of parameters acquired at fixed intervals.

The model was built to perform three (3) major functions: Input data (date fed into the algorithm), train data (data used to operate the algorithm), and feedback data (data used to improve the algorithm). The data set were split into the training and test data in 70:30 percent ratio respectively. the data set were further scaled to values between 0 and 1 before it were inputted into the algorithm. Figure 2 shows the chronological processing architecture in RNN, since RNN structure is comparable to a chain of iterating modules, that can serve as information memory to storage from preceding processing stages. For direct neural networks, its RNNs comprise of a feedback loop used to receive input data that the neural network will process.

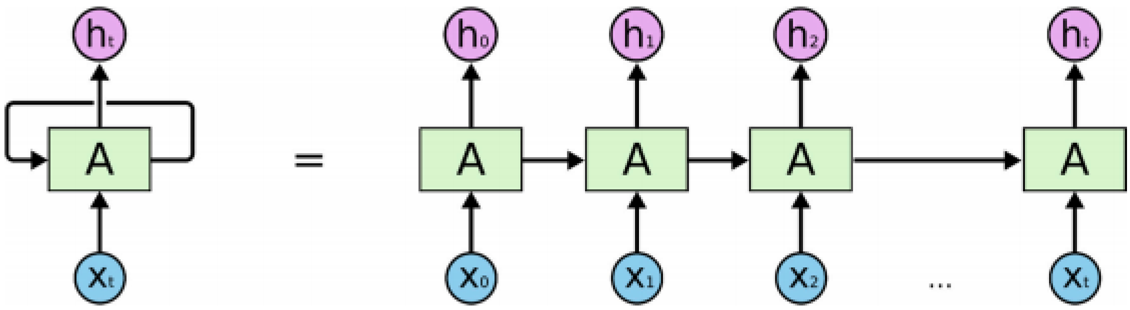

Figure 2. Sample of RNN processing architecture [16]

2.2 Data used for the proposed Model

The ESP system consists of an internal electric motor that is located at the production tubing inside the wellbore. It is power-driven by underground electric cables linked to installations at the surface. The centrifugal pump serves as the engine which is responsible for pumping liquids from the subsurface to the surface facility. This system uses a motor to convert electrical energy into mechanical energy, which is transferred to the liquid in the form of pressure using a centrifugal pump. The reliability of artificial lift systems (such as ESPs) is largely dependent on the outputs of these pumps. ESP can function in harsh environments such as viscous flow and two-phase flow. In the current decade, machine learning algorithms studies have spurred real- time technologies research interest due to their abilities to predict future outcomes using already existing data sets [17]. There variables often affect the performance and operation life-time of the ESP; but, the variables considered in this study for predicting ESP failures are: the vibration data (Figure 3) because mechanical models for vibration of typical faults can positively identify the faults of ESP [18], pump intake pressure, pump discharge pressure, pump frequency, average variable-speed drive, and motor temperature. Operating beyond certain limits of these variables can result in ESP malfunctions or shorten service life, which has a significant economic influence, due to the cost acquired in changing the pump and lost production time which has huge implications.

Figure 3. Vibration Data Chart for Oil Field Operating ESP

2.3 Use of Variable Speed Drive (VSD) Unit

The purpose of the artificial lift design is to create a lifting system that will provide the ideal fluid producing capacity that equals the rate of inflow from the wellbore reference. A shared resolution for over-designed ESP schemes is to install production chokes at the well-head. Installing a choke creates a pressure drop that limits the amount of fluid flowing from the well and rate at which the ESP operates within the acclaimed range of pumping rate. The field considered in this study had a VSD available, thus, the removal of the choke as a means of adjusting the pumping rate. Table 1 shows that as the VSD maintained the electrical frequency driving the ESP system to 52 Hz, the intake pressure of the pump require to produce the desired discharge pressure were within a specific range.

Table 1. Sample ESP Field Data

Date/ Time	Average Variable Speed Drive	Pump Intake Pressure	Pump Discharge Pressure	Pump Frequency	Motor Temperature
20/07/2017 00:31:02	156	1179.8	1613.5	52	130.6
20/07/2017 01:01:02	156	1180	1616.5	52	130.2
20/07/2017 01:31:02	156	1180.4	1617.4	52	130.62
20/07/2017 02:01:02	156	1180.5	1618	52	130.62
20/07/2017 02:31:02	156	1180	1615.5	52	130.57
20/07/2017 02:57:02	156	1180.2	1615.8	52	130.62
20/07/2017 03:27:02	156	1180.5	1615.2	52	130.85
20/07/2017 03:57:02	156	1179.7	1615.4	52	130.71
20/07/2017 04:27:02	156	1179.8	1611.6	52	130.63
20/07/2017 04:57:02	156	1179.9	1613.1	52	130.7
20/07/2017 05:25:52	156	1180	1615.7	52	130.72
20/07/2017 05:55:52	156	1179.8	1616.5	52	130.66
20/07/2017 06:25:52	156	1179.6	1614.5	52	130.88
20/07/2017 06:55:52	156	1180	1618.7	52	130.89
20/07/2017 07:25:52	156	1179.8	1616.9	52	130.54
20/07/2017 07:55:52	156	1180	1614.7	52	130.28
20/07/2017 08:25:52	156	1180	1613.9	52	130.36
20/07/2017 08:55:52	156	1179.8	1615.4	52	130.13
20/07/2017 09:25:52	156	1179.7	1613.8	52	130.37
20/07/2017 09:55:52	156	1180.3	1616.1	52	130.57
20/07/2017 10:25:52	156	1180	1615.1	52	130.67
20/07/2017 10:55:52	156	1179.8	1613.8	52	130.73
20/07/2017 11:25:52	156	1179.4	1608.3	52	130.72

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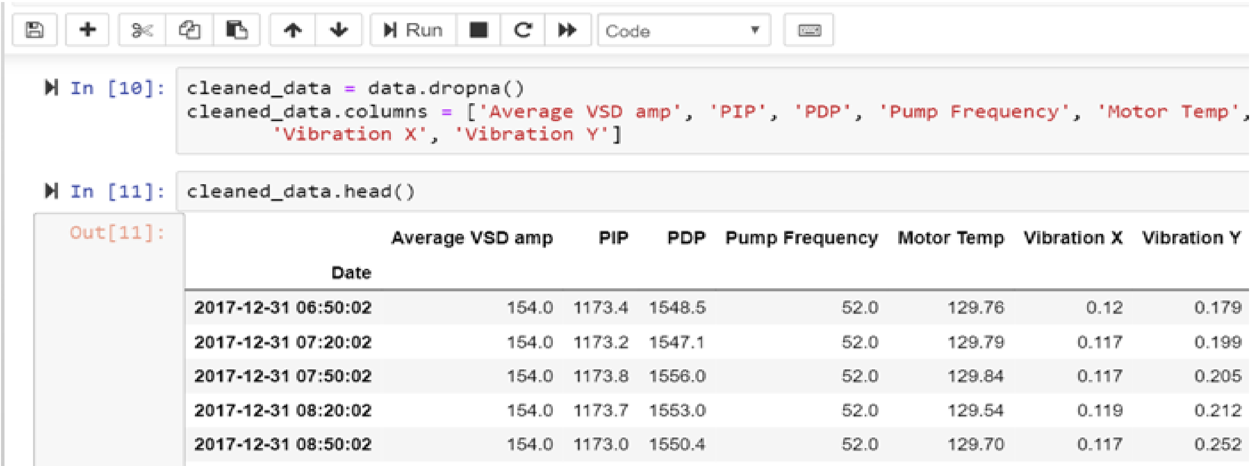
3. Results and Discussion

Jupyter Notebook which is an open-source web-based interactive development environment that permits the creation and sharing of documents was adopted for this study. Field data were imported using the set of codes below in the Jupyter user interface developed in this study due to its ability to support a wide range of workflows in data science and machine learning.

```
#!/usr/bin/env python
# coding: utf-8
# In[1]:
import pandas as pd
import seaborn as sns; sns.set()
import matplotlib.pyplot as plt
import numpy as np
import math
import pickle
# In[2]:
get_ipython().system('pip2 install xlrd')
get_ipython().system('pip3 install xlrd')
# In[3]:
vibration_data = pd.read_excel("E_35_Vibration.xlsx", sheet_name="DATA", index_col=0,
header=1)
surveillance_data = pd.read_excel("E_35_Surveillance.xlsx", sheet_name="Sheet1", index_col=1)
# In[4]:
vibration_data.columns = ['Vibration X', 'Vibration Y']
vibration_data.index.names = ["Date"]
vibration_data.drop([vibration_data.index[0]], inplace=True)
# In[5]:
vibration_data.head()
# In[6]:
surveillance_data.drop(['Unnamed: 0'], axis=1, inplace=True)
surveillance_data.index.names = ['Date']
```

Figure 4 shows the cleaned and filtered data after importation. These data were used to found the connections between the input features and the expected output.



```
In [10]: cleaned_data = data.dropna()
         cleaned_data.columns = ['Average VSD amp', 'PIP', 'PDP', 'Pump Frequency', 'Motor Temp',
                'Vibration X', 'Vibration Y']

In [11]: cleaned_data.head()
Out[11]:
```

Date	Average VSD amp	PIP	PDP	Pump Frequency	Motor Temp	Vibration X	Vibration Y
2017-12-31 06:50:02	154.0	1173.4	1548.5	52.0	129.76	0.12	0.179
2017-12-31 07:20:02	154.0	1173.2	1547.1	52.0	129.79	0.117	0.199
2017-12-31 07:50:02	154.0	1173.8	1556.0	52.0	129.84	0.117	0.205
2017-12-31 08:20:02	154.0	1173.7	1553.0	52.0	129.54	0.119	0.212
2017-12-31 08:50:02	154.0	1173.0	1550.4	52.0	129.70	0.117	0.252

Figure 4. ESP Input Filtered Data in Jupyter Interface

Jupyter interface supports data cleaning and transformation, and these filtered data improve the results of the data-driven model. Due to the number of data set with many columns used for this study, correlation matrix plot in Python was used to check and visualize correlations among columns using a heatmap (Figure 5). The correlation matrix is a matrix in which the i-j position determines the correlation between the i-th and j-th parameters of a given data set. Essentially, there are two key components to the correlation value: size and sign. The larger the size (close to 1), the stronger the correlation. Even if it is negative, there is an inverse correlation; and if it is positive, there is a regular correlation. In the heatmap, Navy blue means positive and White means negative. The stronger the colour (deeper the colour), the larger the correlation magnitude. From Figure 5, there are five (5) regular combination of correlations. These are average VSD amp-pump frequency, pump inlet pressure-motor temperature, pump frequency-average VSD amp and motor temperature- pump inlet pressure. They were identified using the magnitude (1) and colour sign (Navy blue).

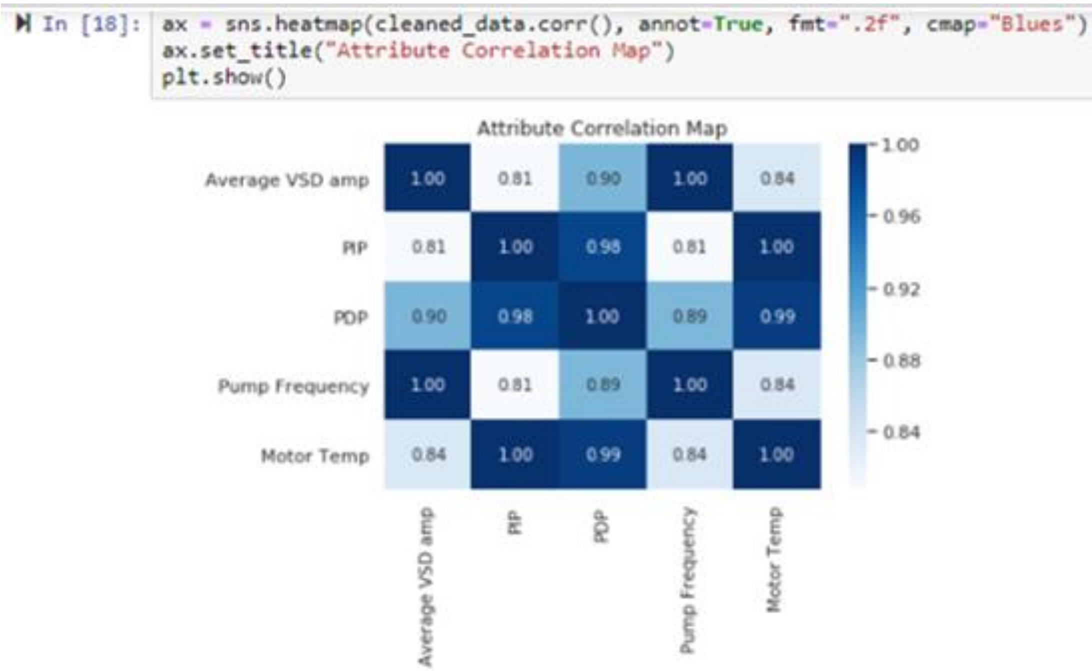


Figure 5. Correlation Heatmap for the Data set

Often, the failure of ESP is observed using the pump discharge pressure, because the pump discharge pressure tends to zero when the ESP is unable to lift the hydrocarbon to the surface. Equation (3) shows that the pump discharge pressure, P_d is dependent on well head pressure, P_{wh} and pressure variation due to hydrostatic and friction forces, ΔP.

$$P_d = P_{wh} + \Delta P \tag{3}$$

Thus, the pressure drop in the production tubing due to failure, shut-down or malfunction of ESP is accounted for when estimating the pressure variation due to hydrostatic and friction forces. This pressure variation has a direct relationship with the pump discharge pressure. From literature, it was assumed in this study that failure is usually caused by previous readings build-ups as shown in Figure 6 [7, 19, 20]. This analytical assumption was the bases for the development of the ESP failure predictive model for pump discharge pressure. The training and validation were conducted using the data that match to the results obtained from the cross-validation. From the simulation analysis results (Figure 6), it can be concluded that the selected algorithm and its corresponding characteristics are fit detecting ESP failures before they happen using build-up data from a particular field.

Date	PDP	Predicted Values
2/28/2018	1548.1	1539.418335
2/28/2018	1553.3	1539.201782
2/28/2018	1543.2	1539.325806
2/28/2018	1555.6	1539.24939
2/28/2018	1551.1	1539.355591
2/28/2018	1556.9	1539.326538
2/28/2018	1553	1539.015137
2/28/2018	0	1538.891357
2/28/2018	0	1538.981201
2/28/2018	0	1539.151489
2/28/2018	0	1539.295898
2/28/2018	0	1271.403076
2/28/2018	0	1271.403076
2/28/2018	0	1271.403076
2/28/2018	0	1271.403076

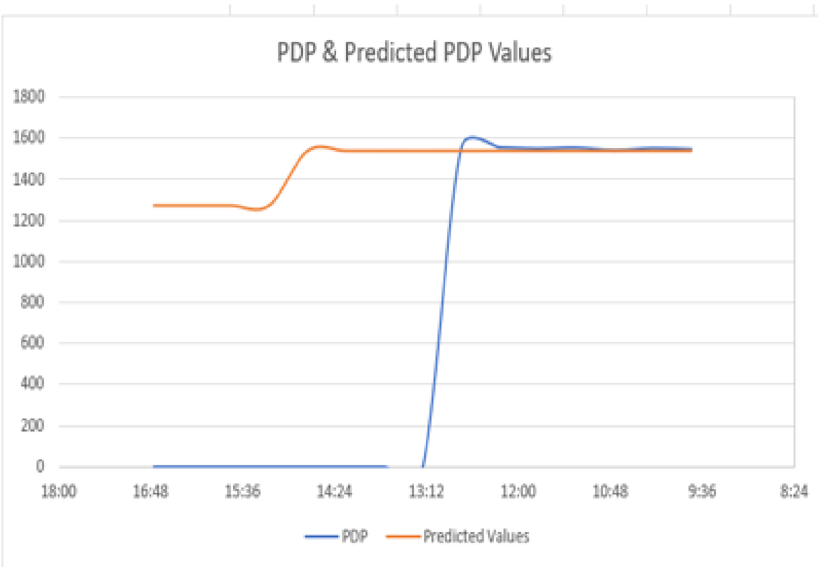


Figure 6. Predicted Failure for the ESP using Pump Discharge Pressure

4. Conclusion

Electrical Submersible Pumps are mainly used to increase hydrocarbon production which in-turn will increase the return on investment, but this function is affected by particulate matters. History has shown that ESPs have short service life. Their failures usually occur unexpectedly and are considered normal since the device is located downhole at the subsurface. Thus, making it difficult to detect the root cause of its short service life. To demonstrate the strictness of this problem, this study examined the Electrical Submersible Pumps (ESPs) failure based on pump discharge pressure. ESPs have been identified as the furthermost artificial lifting devices engaged in hydrocarbon production facilities. To reduce the ESP failures in the field, it is necessary to determine how the operating conditions contribute or behave during ESP failure. Thus, the pump discharge pressure data was used to evaluate the smart model, and this study concludes that:

i. Failure can be instantaneous.
ii. There was very strong correlation in predicting values such as pressure.

iii. The selected algorithm and its corresponding characteristics are fit detecting ESP failures before they happen using build-up data

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